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AUGMENTED COGNITION TRANSITION

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14. ABSTRACT This report details the work done by Honeywell Aerospace Advanced Technology to address two key challenges in the transition of Augmented Cognition (AugCog) technology to the Army's Future Force: 1) integration of the Honeywell AugCog system into the Future Force Warrior (FFW) Soldier system and 2) deployment and evaluation of the dry electrodes for the collection of electroencephalogram (EEG) data under the helmet in an operational environment. Separate evaluations were conducted to test the success of both efforts. The Honeywell team successfully integrated and executed the AugCog hardware and software within the FFW Leader System Software during the U.S. Army's Command, Control, Communication, Computers, Intelligence, Surveillance, and Reconnaissance (C4ISR) 2007 on-the-Move (OTM) Event. The team then collected electrocardiogram (ECG) and EEG data on the third squad leader, during force-on-force exercises, of a signal quality sufficient to classify cognitive state classification in a harsh operational environment. Accordingly, encouraging results showed > 80% classification of workload in the field with EEG alone, thereby advancing the deployability of EEG sensor systems. Together, these successes represent an advance in integration maturity of the AugCog system as it moves towards transition into the Army's future systems.						
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Preface

This report details the work done by Honeywell Aerospace Advanced Technology to address two key challenges in the transition of Augmented Cognition (AugCog) technology to the Army's Future Force: 1) *integration* of the Honeywell AugCog system into the Future Force Warrior (FFW) soldier system and 2) *deployment* and evaluation of the dry electrodes for the collection of electroencephalogram (EEG) data under the helmet in an operational environment. Separate evaluations were conducted to test the success of both efforts.

This work was performed under contract number W911QY-07-C-0037 to the Natick Soldier Research, Development and Engineering Center (NSRDEC) during the period February 2007 to May 2008. Under this contract Honeywell also worked with NSRDEC to develop an AugCog Concept of Operations (CONOPS). The AugCog CONOPS was developed to further explore the potential application and utility of cognitive state information by Army commanders in the field.

Acknowledgments

The Honeywell team would like to thank Mr. Henry Girolamo, the Natick Soldier Research, Development and Engineering Center (NSRDEC) Program Manager, for his steadfast support and guidance. We would also like to thank Dr. Jim Sampson (HFE Consulting) for ensuring that our efforts had operational relevance to the Future Force Warrior (FFW). We also thank Mr. Dennis Magnifico and Mr. Steve Specht for their help in coordinating our integration efforts with the Future Force Warrior (FFW) teams at the On-the-Move (OTM) 2007 experiment.

The Honeywell team acknowledges the efforts of the Honeywell research and development team that supported the running of the various evaluations. We would like to make special mention of the efforts of Mr. Jim Carciofini, Mr. Trent Reusser, and Mr. Bob De Mers in implementation of the software and hardware components of the experimental infrastructure.

We thank Dr. Ken Parham's Battle Lab Integration Team (BLIT), Mr. Fred Dupont, and Mr. Christopher King. In particular, we thank Mr. King for taking the lead on developing an Army exercise that would both meet the soldier's training needs while allowing the Honeywell team to meet their experimental objectives.

Honeywell recognizes Dr. Scott Kerick of ARL (Army Research Lab) HRED (Human Research and Engineering Directorate) for his technical support and guidance during this program.

We acknowledge the tremendous technical efforts executed by the QUASAR team in preparing for and executing the dry electrode test at the Aberdeen Test Center: Dr. Robert Matthews, Dr. Peter Turner, Mr. Tobin McManus, and Mr. Martin Steindorf.

Finally, Honeywell would like to thank the soldiers of the 7th Special Forces Groups who participated in the field test of the dry electrodes at the Aberdeen Test Center. It was a pleasure to work with these fine soldiers, and we would like to recognize them for their professionalism and patience that allowed us to successfully collect the critical experimental data during their training missions.

Executive Summary

Honeywell Aerospace Advanced Technology addressed two key challenges in the transition of Augmented Cognition (AugCog) technology to the Army's Future Force: *integration* and *deployability*. Specifically, efforts focused on (1) integration of the Honeywell AugCog system into the Future Force Warrior (FFW) soldier system, and (2) deployment and evaluation of the dry electrodes for the collection of electroencephalogram (EEG) data under the helmet in an operational environment. Separate evaluations were conducted to test the success of both efforts.

The Honeywell team integrated AugCog hardware and software with FFW leader systems during the U.S. Army's Command, Control, Communication, Computers, Intelligence, Surveillance, and Reconnaissance (C4ISR) 2007 On-The-Move (OTM) Event at FT Dix, NJ. The team then collected electrocardiogram (ECG) and EEG data on the 3rd squad leader during force-on-force exercises. The primary goal was to demonstrate the capability of the AugCog hardware and software system to successfully integrate and execute within the FFW Leader System Software. Honeywell demonstrated a successful integration and achieved a secondary goal of collecting ECG and EEG signals of a quality sufficient to classify cognitive state classification in a harsh operational environment. Based on EEG alone, classification of workload, in the field, exceeded 80% accuracy.

The secondary goal of this project was to advance the deployability of EEG sensor systems. Toward that goal, Honeywell worked with QUASAR to integrate their dry EEG electrodes under a combat helmet, coordinated a field test at the Aberdeen Test Center, and conducted post hoc classification analyses on the collected EEG signals. Together these successes represent an advance in integration maturity of the AugCog system as it moves toward transition into the Army's future systems.

In addition, Honeywell has worked with the Natick Soldier Research, Development and Engineering Center (NSRDEC) to develop an AugCog Concept of Operations (CONOPS). The AugCog CONOPS was developed to further explore the potential application and utility of cognitive state information by Army commanders in the field.

The proposed AugCog System will benefit joint human-automation performance due to the following: shortened decision-making cycle time, decreased task time, increased accuracy of multitask performance, optimized workload to avoid periods of low involvement and extreme engagement by subordinates, reduced cognitive fatigue and stress, and increased support for human involvement at the appropriate level of detail needed for optimal performance. Development of these technologies will provide new capabilities that are required to realize the goal of closing the loop in military operational decision-making for the dismounted soldier.

The success at FT Dix represents an advance in integration maturity for AugCog since the system was previously tested at the Aberdeen Test Center in 2006. During that test, the EEG

and ECG signals were transmitted wirelessly to an off-the-body system; during OTM 2007, the sensing hardware and signal processing software were hosted on the soldier-borne FFW Leader System. Likewise, fielding dry EEG electrodes was another step toward improving the deployability of a sensor-based cognitive state classification system such as the Honeywell AugCog system described in this report.

AUGMENTED COGNITION TRANSITION

1 Introduction

The aim of Augmented Cognition (AugCog) research is to use physiological and neurophysiological sensors to detect, in real time, cognitive states where cognitive resources may be inadequate to cope with mission-relevant demands. Human performance as a function of workload fluctuates subject to fatigue, stress, overload, or boredom. Efforts have focused on ways to leverage cognitive state information to drive adaptive systems to manage information flow when detected human cognitive resources may be inadequate for the tasks at hand.

Work in the field of AugCog began by classifying aspects of cognitive processing (attention, working memory, executive function, and sensory processing) with well-defined, well-understood laboratory tasks (often referred to informally as “Psych 101” tasks). Over the past five years, researchers have moved from the laboratory environment to the field environment, introducing the artifacts (motion, electrical, networking traffic, and disconnect) and stressors (information overload, physical load, competition, and threat of pain) inherent in some operational environments to which AugCog systems would be transitioned. The move from the laboratory to mobile field environments brings several unique challenges that must be addressed if cognitive state assessment is to be used successfully during mobile tasks. Tough sacrifices need to be made, with limitations on the sensors to be used, processing power, and knowledge of the task environment

From the start of the program, the Honeywell AugCog team worked closely with the U.S. Army to address the problem of information overload, expected to occur with the deployment of future Command, Control, Communications, Computers, Intelligence, Surveillance, and Reconnaissance (C4ISR) technologies. The Honeywell team has worked to apply AugCog technologies to the Future Force Warrior (FFW) domain of the individual soldier. FFW will require an AugCog capability to manage information overload during operational task performance—because soldiers within future units of action will be required to process more information afforded by C4ISR, assume more complicated decision-making responsibility (e.g., calling in netted fires), and manage multiple organic autonomous assets (e.g., armed unmanned air vehicle, robotic mule) within fast-paced, dynamic military operations in urban terrain (MOUT).

Current work has focused on transition challenges, in addition to developing wireless and wearable components for sensing soldier states and supporting interactions with information devices, supporting mobile users in physically taxing environments, enabling multitasking in an environment where mission and task priorities can change frequently and rapidly, detecting and managing information overload conditions, and supporting complex decision-making responsibilities. To realize both the AugCog and FFW Advanced Technology Demonstration (ATD) goals, Honeywell addressed two principal objectives to move forward on the path of transition: *integration* and *deployability*.

Specifically, efforts focused on (1) integration of the Honeywell AugCog system into the FFW soldier system, and (2) deployment and evaluation of the QUASAR dry electrodes for the collection of EEG under the helmet. Separate evaluations were conducted to evaluate the success of both of these objectives.

In addition, Honeywell has worked with the Natick Soldier Research, Development and Engineering Center (NSRDEC) to develop an AugCog Concept of Operations (CONOPS). The AugCog CONOPS (see Appendix B) was developed to further explore the potential application and utility of cognitive state information by Army commanders in the field.

The proposed AugCog system will benefit joint human-automation performance due to the following: shortened decision-making cycle time, decreased task time, increased accuracy of multitask performance, optimized workload to avoid periods of low involvement and extreme engagement by subordinates, reduced cognitive fatigue and stress, and increased support for human involvement at the appropriate level of detail needed for optimal performance.

Development of these technologies will provide new capabilities that are required to realize the goal of closing the loop in military operational decision-making for the dismounted soldier.

Section 2 of this report describes the generalized Honeywell AugCog system architecture. Section 3 describes how that system was integrated into the FFW Early Increment Leader System. Section 4 describes the evaluation of the integrated system at the On-The-Move (OTM) technology demonstration. Section 5 describes the integration and evaluation of dry electrodes technology. Section 6 discusses next steps.

2 System Description

2.1 General Architecture

The Honeywell closed-loop integrated prototype (CLIP) is depicted in Figure 1.

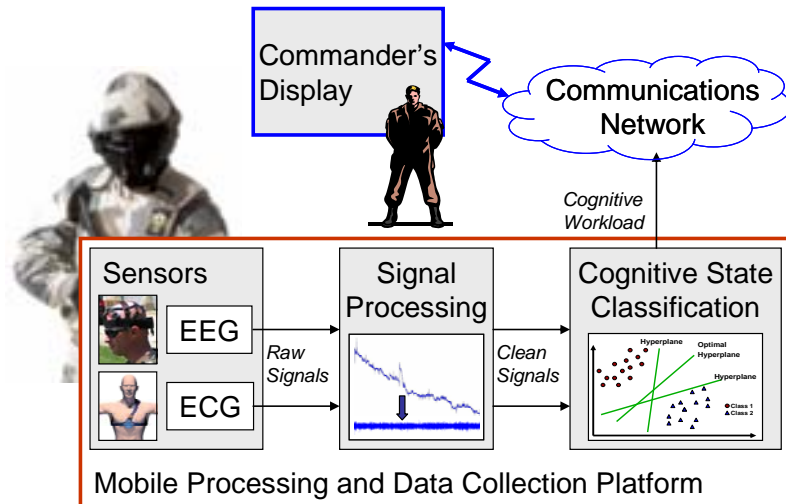


Figure 1. CLIP demonstration architecture.

Physiological and neurophysiological sensors collected real-time data. These raw signals were processed to remove artifacts due to noise, motion, and the environment. After signal processing, the clean signals were classified into levels of cognitive states of interest. Honeywell has focused on classifying cognitive workload. Cognitive workload of the soldier was sent over a communications network to be displayed on the Commander's Display. The commander then determined if any mitigation was needed.

2.1.1 Sensor Hardware

Each participant was outfitted with an Advanced Brain Monitoring, Inc. (ABM) EEG system, a Vital Signs Detection System (VSDS) for cardiac data, and a wireless microphone for recording ambient noise and verbal communications.

2.1.1.1 ABM EEG System

EEG data were collected from the ABM EEG sensor headset (Figure 2). The sensor headset acquired six channels of EEG using a bipolar montage. Differential EEG were sampled from bipolar channels CzPOz, FzPOz, F3Cz, F3F4, FzC3, and C3C4 at 256 samples per second with a bandpass from 0.5 and 65 Hz (at 3-dB attenuation) obtained digitally with Sigma-Delta analog-to-digital (A/D) converters. Data were transmitted across a Bluetooth radio frequency (RF) link to the collection laptop via an RS-232 interface.



Figure 2. ABM's wireless EEG sensor headset.

The sensor headset was developed by ABM as a portable system to record EEG signals. The headset fit snugly on the head and housed EEG sensors like many Food and Drug Administration (FDA) approved laboratory EEG systems, such as the Quick-Cap by Neuromedical Supplies or the Electro-Cap by Electro-Cap International. Physiological recordings were made with an experimental seven-channel digital physiological recorder with low-powered EEG and electrooculogram (EOG) amplifiers designed specifically for ambulatory recordings. The analog box included input jacks for the electrode leads that carried event markers, an on/off switch, amplifiers, and optical isolation designed to meet UL544 requirements. The analog box was coupled to a Real Time Devices microcomputer (commercially available model DSi486SLC, State College, Pennsylvania), which provides A/D conversion, operates the data acquisition software, and stores the data to hard drive.

2.1.1.2 Hidalgo Vital Signs Detection System (VSDS)

The VSDS (Figure 3) measured heart rate, respiration rate, and body motion and position. The VSDS (Bluetooth-enabled version) came with a Bluetooth (Mini Mitter Co. and Hidalgo Ltd.) radio that operated in full disclosure mode. In this mode, both waveform and summary data were transmitted across a Bluetooth communications link. The AugCog system utilized the ECG waveform (two views, sampled at 256 Hz) and the three-axis accelerometry waveform (sampled at 25.6 Hz) signals.

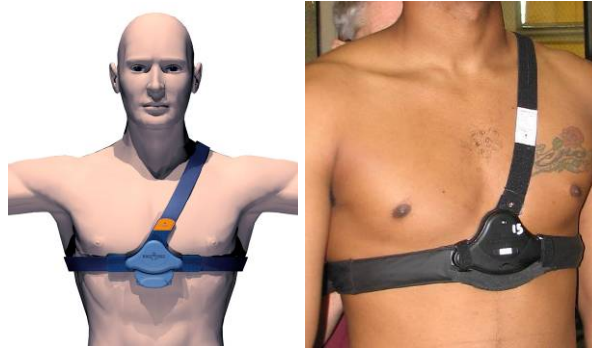


Figure 3. Hidalgo Vital Signs Detection System (VSDS).

2.1.2 Signal Processing

Conducting military maneuvers in operational environments (e.g., urban terrain) often does not allow an individual to remain stationary and can demand simultaneous cognitive and physical activity. Inferring cognitive state from noninvasive neurophysiological sensors is a challenging task even in pristine laboratory environments. Artifacts ranging from eye blinks to muscle artifacts and electrical line noise can mask the subtle electrical signals associated with cognitive functions of interest. These concerns were particularly pronounced in the context of the dismounted ambulatory soldier. For instance, difficulties related to processing of EEG signals in real-world settings include factors associated with both participant motion and the operational environment itself. Specifically, artifacts related to participant motion include high-frequency muscle activity, verbal communication, and ocular artifacts (consisting of eye movements and blinks), whereas artifacts related to the operational environment include electrical noise that creates interference with the EEG signal. Thus, utilization of research methods involving EEG in operational environments necessitates the use of real-time algorithms for signal detection and removal of artifacts. Although real-time signal processing and classification of the EEG has been implemented previously, the Honeywell team was the first to realize this classification in a truly mobile, ambulatory environment with dismounted soldiers (Dorneich et al., 2007).

The ABM system supported an independent signal processing stream. Quantification of the EEG in real time was achieved using signal analysis techniques that identified and decontaminated eye blinks and identified and rejected data points contaminated with electromyographic (EMG) artifacts, amplifier saturation, and/or excursions due to movement artifacts (see Berka, Levendowski, Cvetinovic, Petrovic et al., 2004, for a detailed description of the artifact decontamination procedures). Decontaminated EEG was then segmented into overlapping 256-data-point windows called overlays. An epoch (the temporal window of analysis) consisted of three consecutive overlays. Fast-Fourier transform (FFT) was applied to each overlay of the decontaminated EEG signal multiplied by the Kaiser window ($\alpha = 6.0$) to compute the power spectral densities (PSDs). The PSD values were adjusted to take into account zero values inserted for artifact-contaminated data points. The PSD between 70 and 128 Hz was used to detect EMG artifacts. Overlays with excessive EMG artifacts or with fewer than 128 data points were rejected. The remaining overlays were then averaged to derive PSD for each epoch with a 50% overlapping window. Epochs with two or more overlays with EMG or

missing data were classified as invalid. For each channel, PSD values were derived for each 1-Hz bin from 3 to 40 Hz and the total PSD from 3 to 40 Hz. Relative power variables were also computed for each channel and bin using the formula (total band power/total bin power).

2.1.3 Real-Time Cognitive State Classification

The use of EEG as the basis for cognitive state assessment was motivated by characteristics such as good temporal resolution, low invasiveness, low cost, and portability. While EEG offers several benefits, there were shortcomings that were addressed by this research effort, including the noise artifacts described above and the non-stationarity of neural signals over time (Popivanov & Mineva, 1999). Despite these challenges, research has shown that EEG activity can be used to assess a variety of cognitive states that affect complex task performance. These include working memory, alertness, executive control, and visual information processing. These findings point to the potential for using EEG measurements as the basis for cognitive state assessments in complex task environments such as dismounted soldiering.

Estimates of spectral power formed the input features to a pattern classification system. The classification system used parametric and nonparametric techniques to assess the likely cognitive state on the basis of spectral features, i.e., to estimate $p(\text{cognitive state} / \text{spectral features})$. The classification process relied on probability density estimates derived from a set of spectral samples. These spectral samples were gathered during the same field mission as the other samples that would be used to evaluate classification performance.

The classification system utilized a support vector machine to discriminate between low and high task load. Support vector machines are linear classifiers that use a quadratic optimization procedure to find an optimal orientation and location for a discriminating hyperplane between two classes of data. The optimization procedure finds a location and orientation for the hyperplane that lies as far away as possible from examples in each class that were likely to be confused with each other (see Figure 4).

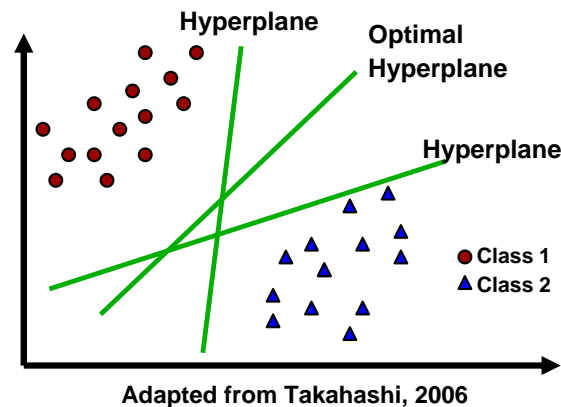


Figure 4. Hyperplane orientation.

Separating hyperplanes identified using this procedure has been shown to maximize generalization performance (Vapnick, 1999). Although they were linear classifiers, support vector machines were used to solve nonlinear problems by means of the so-called kernel trick. Data that may not have been linearly separable in the original feature space were projected into a high-dimensional space where the data may be linearly separable (Figure 5). The support vector machine used in this effort employed a radial basis function kernel with a kernel parameter of 1 and a slack parameter of 0.05.

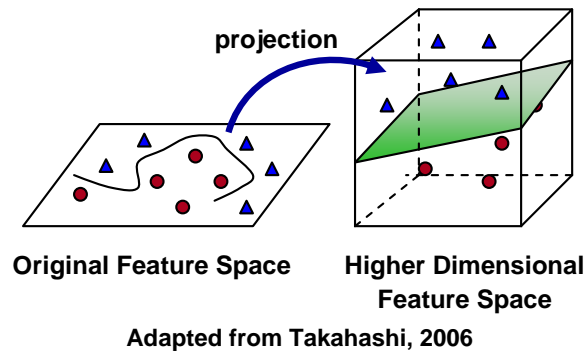


Figure 5. Kernel trick projection to higher dimensional space.

2.1.4 Mobile Processing Platform and Communications Network

Ideally, to enable maximum mobility, all the processing power needed to collect and process the sensor data should be located on the body of the soldier. In addition to logging the data, the raw sensor data were processed by the signal processing algorithms to produce a clean signal for Honeywell’s cognitive state classification algorithms. That cognitive state assessment was transmitted via a communications network to “publish” the information for wider use.

2.1.5 Commander’s Display

Experiments in previous phases explored the feasibility and utility of “closing the loop” by providing a company commander (CO) with real-time cognitive state information of subordinate platoon members (Dorneich et al., 2007). This was operationalized by displaying cognitive state information to the CO to allow them to adjust the flow of communications to better match the subordinates’ current capacity to process information. In previous evaluations, Honeywell explored using automation to close the loop, where the automation was driven by assessments of cognitive state (Dorneich et al., 2006; Dorneich et al., 2005). In the 2006 evaluation, the loop was closed by a human leader using cognitive state feedback of subordinates and then modifying the information flow to those subordinates. This mitigation strategy most closely aligned with the interests of the FFW ATD, which saw cognitive state feedback as useful information for a leader when assessing the combat readiness of his or her troops.

3 Integration with FFW

3.1 Overview

The primary goal of this phase of the project was to integrate the Honeywell AugCog system into FFW systems. Specifically, the project worked toward full integration into the FFW Early Increment 2 Leader System for demonstration in the C4ISR OTM technology demonstration at FT Dix, New Jersey, in July 2007 (see Figure 6).

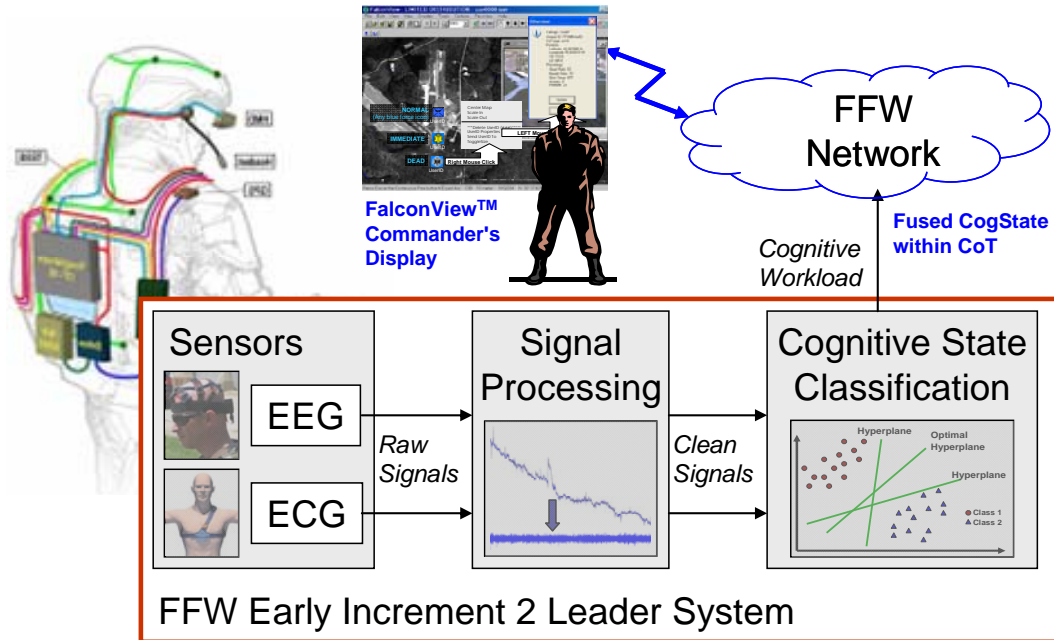


Figure 6. Honeywell AugCog system integrated into the FFW Network.

3.1.1 Mobile Processing Platform and Communications Network

The Early Increment 2 Leader System package was a soldier-worn hardware and software ensemble that provided next-generation digital capabilities to the dismounted soldier (see Figure 7). The core of this system was the Panasonic CF-18 Toughbook laptop that supported processing and the ITT Wearable Soldier Radio Terminal (WSRT) that provided voice and data communication to the FFW Network. The Honeywell signal processing and classification software was hosted on the CF-18, and the output of this software was formatted as a cursor-on-target (CoT) message (standard information schema that supported information interoperability and presentation of information on all FalconView™ displays) and transmitted across the FFW Network via WSRT radios.

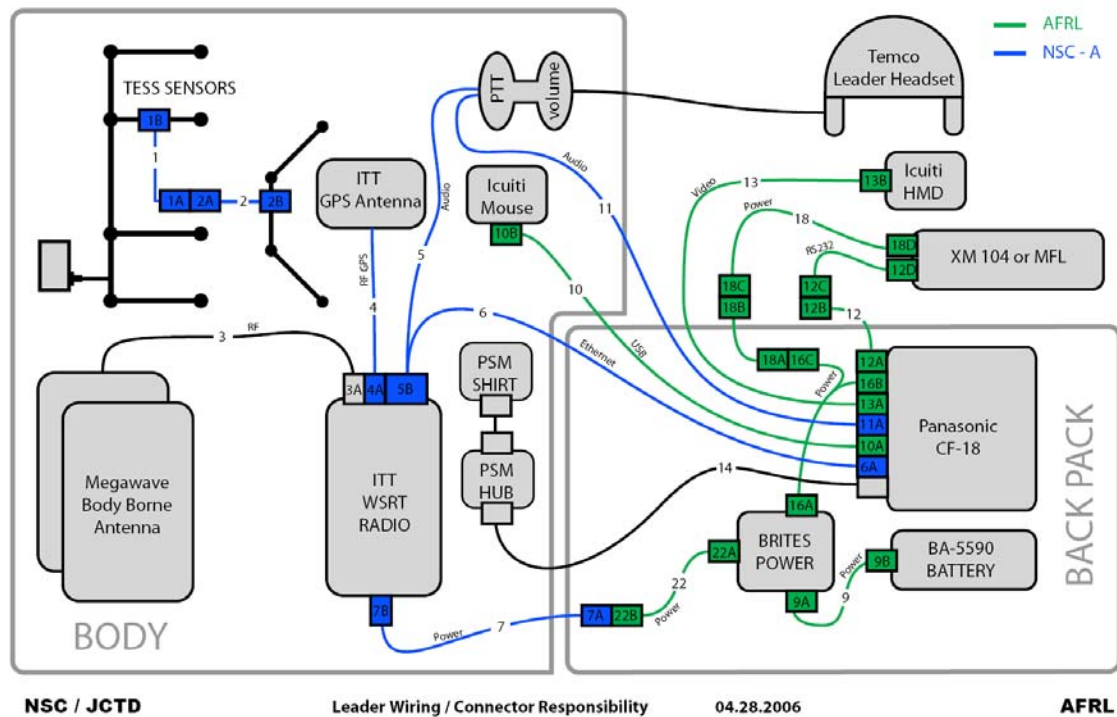


Figure 7. The FFW Early Increment 2 Leader System.

3.1.2 Commander's Display

Cognitive state assessments of a soldier were published over the FFW Network in CoT format for display on a Commander's FalconView™ display. Since there is no standard symbology definition for the individual soldier level, let alone for cognitive state feedback, symbology was proposed and implemented for the OTM demonstration. These symbols are shown in Table 1. See Appendix C for the derivation of AugCog symbology that follows tactical symbol conventions from the Common Warfighting Symbology from MIL-STD-2525B (Department of Defense, 1999).

Table 1. Tactical symbols for cognitive state feedback.

Cognitive State	Low Workload	Medium Workload	High Workload	System Fault Alert
Symbol				

4 OTM Experiment

4.1 OTM Overview

In 2007, the U.S. Army held the C4ISR OTM technology demonstration at FT Dix, New Jersey. The goal was to showcase innovative technologies that would improve soldiers' effectiveness by increasing their situation awareness in battlefield environments (see Figure 8). The OTM involved FFW Experimental Force (EXFOR) soldiers in realistic war game scenarios, utilizing more than 100 live communication, sensor, and battle command systems (CERDEC, 2007).

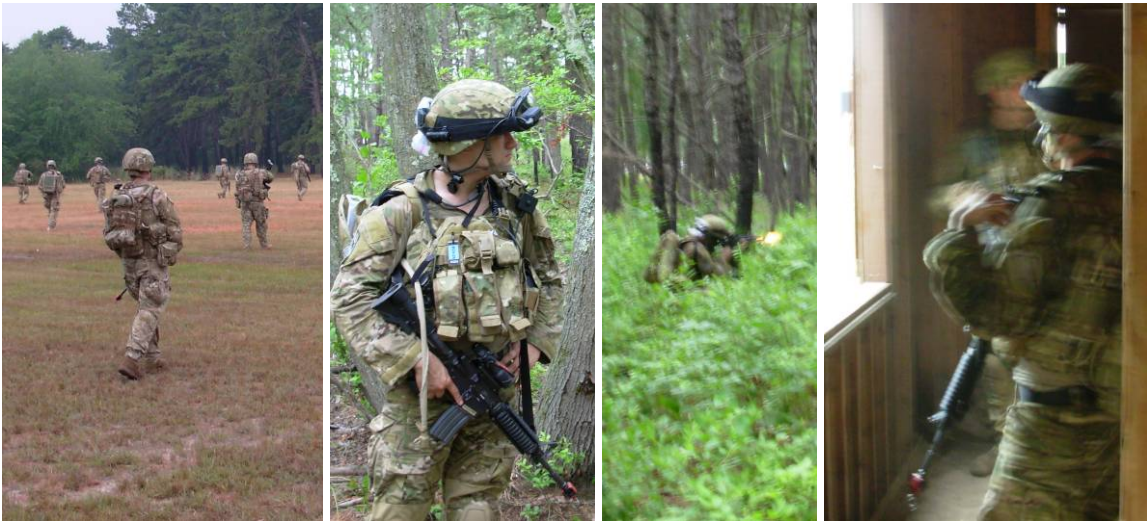


Figure 8. OTM Event at FT Dix, New Jersey.

4.2 Honeywell Participation

The Honeywell/NSRDEC team integrated AugCog hardware and software with FFW Leader Systems during the 2007 PM C4ISR OTM event. The team then collected ECG and EEG data on the third squad leader during force-on-force exercises that were conducted on July 19, 2007, at FT Dix. In addition to satisfying the integration goal of this program, Honeywell's participation at OTM provided an additional opportunity to evaluate the ability to distinguish between low and high cognitive task load in an operational setting. The ability to reliably differentiate these two states could be leveraged for operational advantage to augment the commander's awareness of the state of his subordinates, as well as serving as input to future adaptive systems that could tailor information presentation and management to the state of the recipient. This section documents the classification approach and results.

The AugCog system was tested and data were collected during two OTM exercises that involved live, virtual, and distributed assets. On the first day, the platoon conducted a phased attack on a MOUT site, which was defended by the opposing force (OPFOR). The second day of data collection involved a six-hour mission where the platoon first approached the objective in High Mobility Multipurpose Wheeled Vehicles (HMMWVs),

dismounted, and moved to the objective rally point (ORP), which they took by force. The third squad leader participated in a leader recon, where the platoon leader led his squad leaders to reconnoiter the objective. Rather than returning to the ORP, the leaders utilized their FFW systems to relay the plan electronically to the platoon, which then moved up to take positions per the plan. The third squad was tasked with leading a feint to divert the OPFOR attention before the main force attacked the MOUT site. The OPFOR were holding hostages, so there was a mix of OPFOR and civilians in the battlespace. The third squad eventually attacked and occupied a building by force before they placed unattended ground sensors for remote monitoring.

4.3 Equipment Setup

The AugCog team collected EEG signals from ABM's wireless EEG sensor headset, which was integrated under the FFW helmet (see Figure 9); ECG data from Hidalgo's Vital Signs Detection Unit, part of the U.S. Army's Warfighter Physiological Status Monitoring program, were also collected and fused with the EEG signals in order to classify real-time cognitive state information. Utilizing the FFW CF-18 Toughbook computer as a processing platform, signal processing algorithms cleaned the sensor signals so that advanced algorithms could status the third squad leader's cognitive state on a moment-to-moment basis. The resultant cognitive state assessment information was then formatted in the CoT XML tags needed to push the information over the FFW network to support the display of AugCog state information on FalconView icons that were viewable by those superior to the sensed soldier, platoon leader, and platoon sergeant.



Figure 9. EEG setup.

4.4 Research Objectives

The primary goal of the AugCog-OTM experiment was to demonstrate the capability of the AugCog mobile system to deliver robust ECG and EEG signals and to classify cognitive state classification in a harsh operational environment. The cognitive state classification would output an assessment of cognitive workload into one of two levels: *low workload* and *high workload*. The two levels of workload were defined operationally.

The soldiers were experiencing *low workload* when they had spare capacity to handle task demands. In low workload, the soldier could take on additional tasks without compromising performance on current tasks. Low workload did not mean that the soldier was doing nothing; rather, the soldier was handling the current task load well and could take on additional tasks. Examples included mission lulls or the mission being executed flawlessly with little variation from the preplanned, well-versed drill.

The soldiers were experiencing *high workload* when the task load maximized or even exceeded the soldier's cognitive capacity. The soldier absolutely could not take on an additional task without compromising performance on current tasks, and current task performance was possibly suboptimal due to excessive cognitive demands. Examples that drove workload into the high range included unexpected and unplanned events that required rapid replanning and extensive coordination by the leadership.

4.5 Classification Approach

The Honeywell classification approach used EEG PSD features, decomposed into the different clinical bands, as input to the classifier. The EEG PSD features that form the basis for classification contain information pertinent to the classification of cognitive states, as well as irrelevant components and noise. Accurate classification of workload based on EEG called for a system that could estimate workload by identifying dimensions or features of EEG that were informative with respect to distinctions among workload levels. The analysis relied on the logistic classifier. A logistic classifier assumes that the relationship between a set of independent variables (EEG features in this context) and the estimated probability of membership in a class (high or low workload) can be modeled in terms of a sigmoid function: $P(c|y) = 1/(1+e^y)$. Model parameters were identified using maximum likelihood estimation. The decision boundary created by this classifier was linear. Linear classifiers are widely used by EEG researchers as their inherently low complexity limits the possibility of overfitting — an issue of concern in artifact-rich mobile task contexts.

4.6 Data Analysis Methodology

4.6.1 Ground Truth

The first step in evaluating a classification system in the field is to collect data during the exercise that can establish ground truth for the phenomenon of interest. In this case, disparate task loads experienced by soldiers in the field, i.e., low and high task loads, were of interest. Accordingly, a videographer was deployed to record the activities of the third squad leader while he conducted a force-on-force mission in the pine barrens of FT Dix, New Jersey. Next, multiple expert reviewers analyzed the video footage to identify periods of high and low task load. These reviewers used the following criteria to select suitable periods:

- Sustained periods (> 5 minutes) of consistent task load
- Periods that did not contain transitions from low-to-high or high-to-low task load
- Good EEG signal quality during the period

It is worth noting that the analysis was not constrained by ECG signal quality, since the battery in the Wearable Physiological Status Monitor (WPSM) died prior to the end of the long exercise. As a result, all classification results presented here were based on EEG data only.

4.6.2 Classification Metric

A metric used to evaluate classification performance was the area under the Receiver Operating Characteristic (ROC) curve (see Duda, Stork, & Hart, 2001). ROC curves plot true positives (on the y-axis) against false positives (on the x-axis) as a threshold for discriminating between targets and distracters. The ROC curve provides a way to assess the degree of overlap between two univariate distributions. It is widely used to evaluate human and machine signal detection capabilities. The ROC curve provides a way to assess the degree of overlap between the outputs of a classifier for two classes of data. Perfect classification produces an area under the curve value (A_z) of 1.0, while chance performance produces an A_z value of 0.5.

In noisy operational environments, EEG and other electrophysiological sensors can be compromised by noise over short temporal windows. One strategy for dealing with momentary fluctuations in classification accuracy is to median filter the output of the classifier over different time windows. One consequence of such temporal smoothing of classifier output is that it may introduce a lag in the decision process. The analysis must consider the tradeoff in accuracy as the temporal window of output smoothing is varied (Dorneich et al., in press). This strategy assumes that task demands remain stable over the span of the smoothing window. Smoothing was accomplished using a median filter on the output of the classifier over specific time windows. The analysis considered the tradeoff in accuracy as the temporal window of output smoothing was varied.

One way to explore the bias and variance of a classifier is through a process called n-fold cross-validation. This procedure entails splitting the data into n subsets. At each iteration of the validation procedure, one of these subsets (n_i) was used for testing the classifier, while the remaining $1 - 1/n$ sets were used for training the classifier. A typical choice of n is 10. Estimates of bias and variance get more conservative as the size of n decreases—the classifier has to be trained with less of the data and is assessed by generalizing to a larger subset of unseen data.

Classification performance was assessed using cross-validation. With 10-fold cross-validation, the data set was split into 10 subsets. Over the course of 10 iterations, a new subset was picked to serve as testing data, while the remaining 9 subsets served as the training data.

4.7 Results

4.7.1 Ground Truth

After expert review of the video, two periods each of low and high task load were identified, as shown in Table 2.

Table 2. Periods of identifiable high and low task load.

Task Load	Duration (mm:ss)	Description
High	05:15	Squad leader was leading a detailed mission planning session with his team leaders immediately prior to attack.
Low	08:09	Squad leader was waiting for platoon leader to return.
Low	09:45	Squad leader was sitting quietly.
High	07:57	Squad leader was positioning his men during early phases of attack. He was also firing on enemy targets and coordinating ongoing activities.

In addition to assessing the cognitive task load of each segment, pains were taken to select those segments of relatively low physical activity (e.g., standing, crouching) and to equate the activity level between the selected low- and high-workload periods. Primarily this was done to provide the best quality EEG signals for the classification analysis. This was also done to eliminate a spurious data source (i.e., motion artifacts) that could inadvertently drive the classification results, even though it has been previously demonstrated that the Honeywell classification approach was not driven by physical activity (Dorneich et al., 2007).

4.7.2 Classification Results

The results presented here were from EEG-based classification only since the VSDS' battery died prior to the critical high-workload periods near the end of the six-hour mission. For any classifier to work, there need to be differences among the features for the classes of interest, in this case, low and high task load. To highlight the inherent differences, the feature outputs were normalized and plotted against the six bipolar channels (C3C4, F3Cz, FzC3, CzPO, F3F4, FzPO) across the clinical bands (delta, theta, alpha, beta, and gamma). Figure 10 illustrates that there was separation in the average power between workload levels in all channels, and across all bands, which formed the basis of the classifier's ability to distinguish between workload levels.

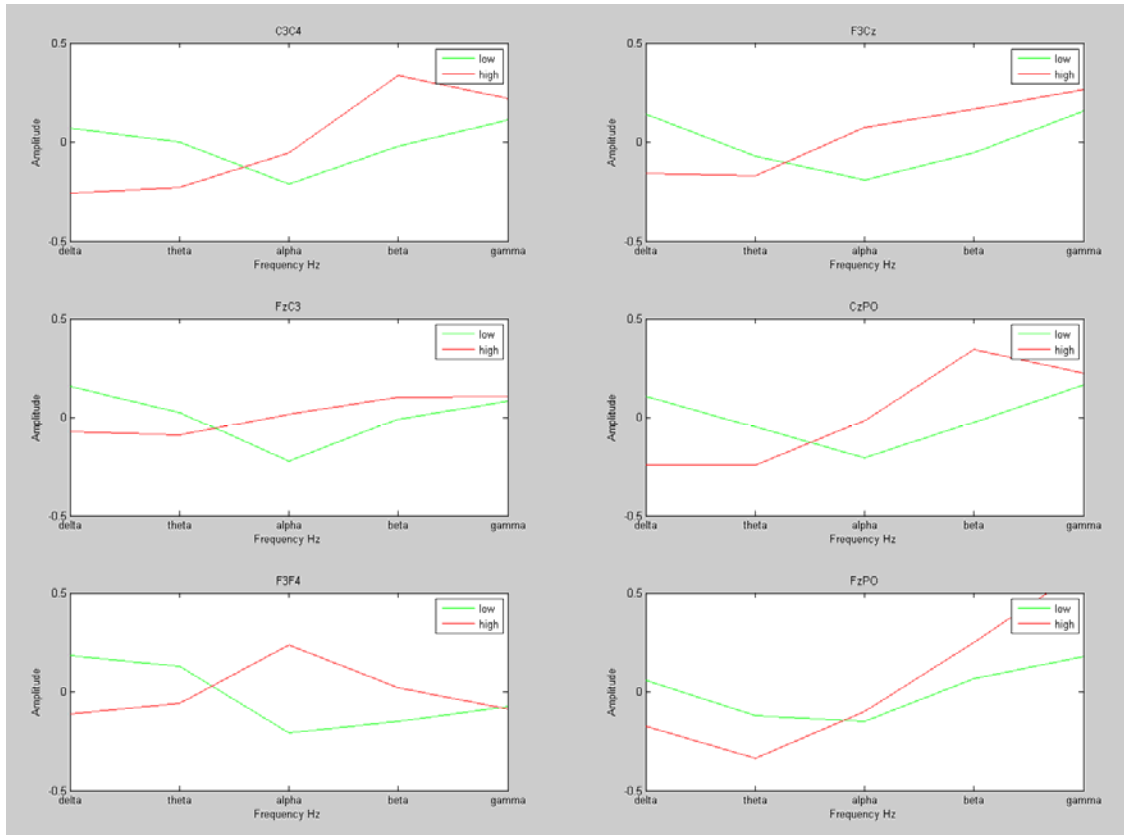


Figure 10. Feature amplitude by clinical band for all six channels of EEG.

Figure 11 presents the classification accuracy as a function of the temporal smoothing window.

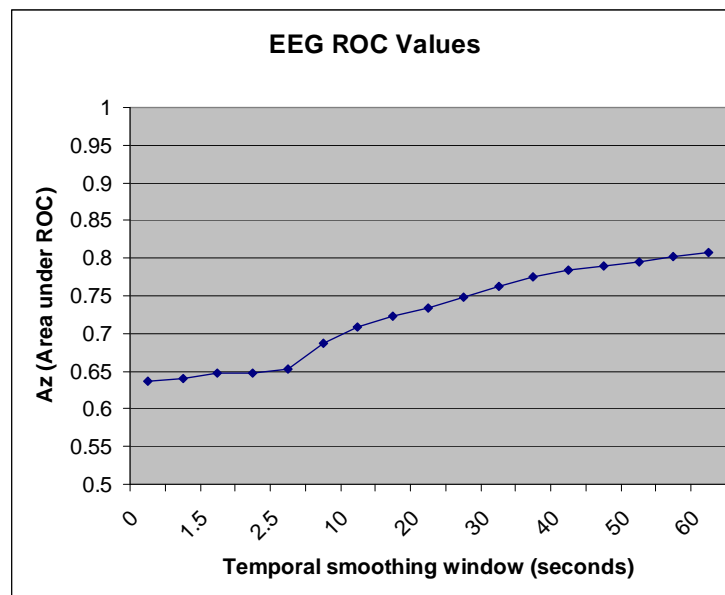


Figure 11. Classification accuracy as a function of temporal smoothing.

Temporal smoothing up to one minute was investigated. Classification accuracy rose monotonically up to a one-minute-long temporal smoothing window; however, the rate at which temporal smoothing benefited accuracy appeared to diminish as window sizes increased. Given the criteria in workload period selection, it was likely that task demands remained stable up to the one-minute window.

5 Dry EEG Electrode Evaluations

5.1 Motivation

The second goal of this project was to advance the deployability of EEG sensor systems. Toward that goal, Honeywell integrated the QUASAR RF dry EEG electrodes under a combat helmet in the Honeywell AugCog system. This moved the system that much closer to a deployable setup. The OTM 2007 EEG data were collected with a conventional “wet” electrode setup that required the application of electrolyte gel, which has obvious soldier acceptability and logistical issues. The QUASAR dry electrode system delivered low size, weight, and power performance and was designed with suspension under the helmet to maximize isolation from helmet motion. This improved signal quality and soldier comfort. The combination of NSRDEC’s domain expertise and strategic leadership, Honeywell’s signal processing and classification algorithms, and QUASAR’s deployable dry EEG sensor supported a compelling AugCog offering with superior soldier acceptance and utility.

5.2 QUASAR Dry Electrodes

EEG data were collected from a QUASAR’ EEG sensor headset (see Figure 12). The sensor headset acquires six channels of bipolar montage EEG data using eight sensors. Differential EEG were sampled from bipolar channels CzPOz, FzPOz, F3Cz, F3F4, FzC3, C3C4, and a reference sensor at P4, all at 240 samples per second with a signal bandwidth from DC to 100 Hz. Data were transmitted across a 2.4-GHz wireless link (similar to 802.11g in character) to a base station and then the collection laptop via a USB interface. Quantification of the EEG data in real time was achieved using signal analysis techniques to identify and decontaminate eye blinks and identify and reject data points contaminated with electromyography (EMG), amplifier saturation, and/or excursions due to movement artifacts.

The military version of the Sensor Headset and wireless data acquisition system developed by QUASAR was made from a modified FFW helmet and harness. This fit snugly on the head and houses EEG sensors like many FDA-approved laboratory EEG systems. Unlike the conventional wet electrode EEG sensors, the QUASAR EEG electrodes were dry and required no prior skin preparation and no conducting gels to operate. Physiological recordings were made with low-powered EEG and EOG amplifiers and 16-bit A/D converters designed specifically for ambulatory recordings. The Sensor Headset was only used for recording physiological signals and did not introduce energy into the body except for very minor electromagnetic radiation typically emitted by small electronic devices. The only risk posed by this device was mild discomfort due to the pressure exerted by the FFW harness and sensors on the user’s head. To minimize this risk, prior studies at QUASAR have assessed comfort and wearing time versus sensor load; the individual sensor loading was adjustable and was measured for each participant prior to testing.



Figure 12. QUASAR's wireless EEG sensor headset.

Two experiments were conducted to assess the viability of the dry electrode technology. The first was a laboratory experiment, followed by a field experiment where the system was used on soldiers performing operational tasks in a training setting.

5.3 Laboratory Evaluation

5.3.1 Research Objectives

The purpose of this experiment was to record EEG data under controlled laboratory conditions using QUASAR's hybrid EEG sensor system (which features dry, wireless silver sensors exhibiting capacitive coupling at low frequencies and resistive coupling at high frequencies) to assess signal quality during the performance of high- and low-workload tasks with helmet on and helmet off under both static and ambulatory conditions.

5.3.2 Method

5.3.2.1 Experiment 1: Auditory N-back Lab

Four participants were tested in two experiments using QUASAR's hybrid EEG sensor system. The first experiment consisted of an n-back test under all combinations of three independent variables workload (low, high), mobility (seated, walking), and helmet (on, off): see Figure 13. The goal was to test artifact reduction methods and workload classification algorithms on spectral features of the data.

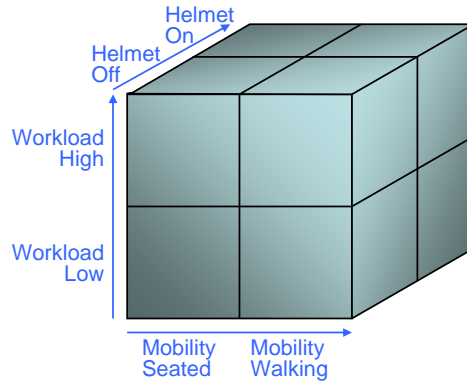


Figure 13. Independent variables in the dry electrode lab evaluation.

The working memory assessment was conducted using an auditory n-back task. The n-back task required participants to process a sequence of letters presented on a computer screen. With every presentation of a letter, the participant had to both encode the letter in memory and indicate whether the letter corresponded to a letter shown n presentations ago. Working memory load encountered by a participant was controlled by manipulating the value of n . For this experiment, the low workload condition was a 0-back test (does the current letter presented match the first letter presented in the entire sequence?). High workload was a 3-back test (does the current letter match the letter from three presentations ago?). Participants responded affirmatively by clicking the left mouse button of a wireless mouse when the current letter matched the target (either the first letter in the sequence for 0-back or the letter presented three presentations ago in 3-back). In the walking trials, participants walked around the perimeter of a medium-sized room (24 x 24 feet) at a regular pace as dictated by a metronome — to ensure that participants walked at the same pace for both low- and high-workload trials (since it was suspected that participants might inadvertently slow down during high-workload blocks as more of their attention was focused on the n-back task). Walking pace was controlled to remove a potential confound with workload level and to control the level of motion artifacts across conditions. Participants listened to the letters played through the PC speakers and responded with a wireless mouse during the walking trials.

5.3.2.2 Experiment 2: Evoked Response Potentials (ERP) Study

The goal of the second experiment was to test the ability of the dry electrode system to detect Evoked Response Potentials (ERP) associated with a Rapid Serial Visual Presentation (RSVP) task. The RSVP task consisted of rapid presentations (every 200 milliseconds) of a series of satellite images with and without relevant missile-launch stimuli (targets). The participant seeing a target provokes an observable ERP which can be related to well-known waveform features revealed in previous research (Mathan et al., 2007).

5.3.2.3 Data Analysis

As discussed earlier, it was important to know how effectively a classification approach can differentiate between classes on a moment-to-moment basis. The ROC-curve metric was used to evaluate classification performance. Ten-fold cross-validation was used to evaluate the classification approach.

5.3.3 Results

Overall, the sensors and hardware/software integration between stimulus presentation and data acquisition systems performed well, and quality EEG data were observed, at least with preliminary subjective analyses, in each of the four participants during both experiments. As with “gold-standard” wet electrode systems, more artifacts were observed during dynamic ambulatory conditions than during seated conditions, and the extent of artifact contamination varied by participant.

5.3.3.1 Auditory n-back Lab Results

Table 3 shows the results from the auditory n-back lab classification. The classification results were obtained using Ten-fold cross-validation and logistic regression. The area under the ROC curve was used as the performance metric. Participants 1 and 4 did not participate in a helmet-off condition due to limited availability.

Table 3. Auditory n-back lab classification results.

Condition	p1	p2	p3	p4
Seated	0.45	0.75	0.74	0.90
Walking	0.89	0.73	0.70	0.70
Helmet Off	x	0.68	0.82	x
Helmet On	0.72	0.71	0.74	0.78
Overall	0.72	0.69	0.72	0.78

It is not clear how to explain Participant 4’s very low classification during seated trials. The best results for the other three participants were obtained during seated trials, as expected given the better signal quality afforded by low levels of mobility. However, the falloff in performance due to motion varied depending on the participant (~0.02 to ~0.21). The results in the “helmet on” condition were comparable with results seen with wet electrodes (Mathan et al., 2007). The overall classification results pooled data from both mobility conditions and both helmet conditions. Performance was in line with what has been seen in previous laboratory evaluations.

5.3.3.2 ERP Study

Table 4 lists the single trial ERP results using QUASAR’s dry electrode system. These results were obtained using a nonlinear support vector machine with 10-fold cross-validation.

Table 4. Classification accuracy for ERP detection.

	p1	p2	p3	p4
Classification Accuracy	0.94	0.74	0.76	0.97

Participants 1 and 4 showed classification performance in line with similar studies conducted with 32 channels of wet electrodes (Mathan et al., 2006); however, participants 2 and 3 were far below the classification level expected for this task. It should be noted that these dry electrodes were only prototypes and that the super-high impedance connection to the participant's scalp was sometimes unstable.

5.3.4 Next Steps

Further analyses were conducted by both Honeywell and NSRDEC to examine strategies for removing artifacts in dynamic mobile conditions (e.g., bandpass filter settings, independent component analysis), and different parameters for applying spectral analyses were discussed (e.g., window length, overlap) in terms of optimizing time/frequency resolution and bias of spectral estimates. Honeywell and NSRDEC coordinated efforts to compare and contrast signal processing techniques that provide optimal data for derivation of ERP (RSVP task) and workload classification (n-back task). QUASAR continued to make improvements to the sensor system in terms of comfort and miniaturization, although the overall consensus was that all parties were confident that the prototype system was ready to be tested in an operational environment on soldiers performing MOUT.

5.4 Field Experiment

5.4.1 Research Objectives

The Honeywell-QUASAR AugCog test event was a joint effort between the Aberdeen Test Center (ATC), Honeywell, QUASAR, and NSRDEC to validate the ability of dry EEG sensors to reliably detect cognitive state signatures in soldiers executing high-fidelity training in an operational environment. The AugCog team conducted field tests of the QUASAR dry electrode system in conjunction with a training event for a 19-man element of the 7th Special Forces Group during the week of March 17, 2008. The objective of the experiment was to test the dry electrode sensor system in realistic conditions, where participants were stressed both physically and cognitively.

5.4.2 Method

5.4.2.1 Schedule of Events

An experienced military trainer conducted the training event as the observer/controller (O/C). The O/C led the troops in training exercises at ATC's Mulberry Point MOUT grounds. The troops received two days of training prior to executing data collection runs with the EEG system in order to familiarize themselves with the facility and reach a certain level of competency in the MOUT skills.

On March 19 and 20, two data runs were conducted, one in the afternoon and one in the evening (see Table 5).

Table 5. Participant schedule.

Time of Day	March 19	March 20
Afternoon	Team Leader 1	Team Leader 2
Evening	Team Leader 2	Team Leader 1

5.4.2.2 Participants

Prior to the start of the training event, the element's leadership and the O/C selected two junior members, who would be leading the training missions, to be instrumented with the EEG system. The decision to assign junior members to the leadership position for the two days of data collection was motivated by the need to induce very high workload during the mission, which may have been more difficult with senior leaders.

5.4.2.3 Tasks

For each of the four data collection runs, the assigned team leader (TL) led 12 soldiers on a mission to "kill or capture an HVT" whose last known location was in one of the buildings in Mulberry Point. Up to six other Special Forces soldiers acted as OPFOR loyal to the high-value target (HVT). The O/C and the element's leadership managed OPFOR activity to achieve the experimental objectives of inducing sustained periods of high and low cognitive workload in the instrumented leader. All soldiers were armed with simunitions (i.e., soap bullets) to increase realism and stress during these missions.

Once the experimental team of Honeywell and QUASAR had instrumented the soldier (see Figure 14) and was ready to record the activity for "ground truth" review, the element's leader briefed the participants on their mission no more than five minutes prior to a required briefing of the soldiers they would be leading.



Figure 14. Preparing soldier participant for data collection.

The TL then briefed his 12-soldier element on his plan for achieving mission objectives. After a short briefing, the TL led his soldiers outside, where he requested radio checks and ordered them to load their weapons. The element was then split into two teams, and each team loaded into its HMMWV for a mounted approach to the objective.

5.4.2.4 Data Collection

Two members of the experimental team “shadowed” the TL to record EEG that was streamed wirelessly from the soldier and to videotape the activity to conduct post hoc “ground truth” assessment of low- and high-workload periods. The O/Cs also followed the movement of the TL to support the deployment of OPFOR.

The missions were very fast paced and involved numerous engagements between OPFOR and Friendly (Blue) Force (BLUFOR). Radio communications were inconsistent due to connectivity issues exacerbated by the metal substructures of most of the MOUT buildings. This effectively induced high workload since the TL had to do more replanning when he was unable to communicate with the other team under his command. During most missions, the TLs led their elements in entering and clearing many buildings (6-10) as they moved toward their objectives and as security required. The TLs also had to deal with wounded and killed soldiers (casualty state determined by the location of the simunition hit).

In each case, the element captured or killed the HVT before receiving authorization to exfiltrate off the objective. Missions were typically a frantic 70-90 minutes of high tempo activities, culminating in a hectic exfiltration by vehicle under heavy fire by OPFOR.

Once BLUFOR arrived back at the homebase building, the TL led an after action review (AAR) with the O/Cs and his element on the mission. The element’s actual leader provided feedback on how the mission was executed. The TL then led a full AAR with the entire element to include the perspective of OPFOR. After the full AAR, the experimental team removed the EEG system and then reviewed the audio/video footage of the mission to allow them to “talk through” the mission with regard to their moment-to-moment mental workload.

5.4.3 Results

A variety of EEG based measures have been shown to be sensitive to variations in workload (e.g., Wilson & Hankins, 1994; Gevins, Smith, McEvoy, & Yu, 1997). EEG sensors, worn on the scalp, record electrical signals associated with neural activity. Signals recorded using these sensors were typically spectrally decomposed for analysis using the FFT. The FFT operation decomposes each waveform into sinusoidal components that were described by three parameters: amplitude, frequency, and phase. The amplitude of EEG over various frequency bands - delta (1 to 4 Hz), theta (4 to 8 Hz), alpha (8 to 13 Hz), beta (13 to 30 Hz), and gamma (30 to 40 Hz) - have been shown to vary in conjunction with different brain states. For example, delta activity is dominant during deep sleep, alpha activity is typically observed during wakeful but relaxed states, and beta and gamma activity is prominent during problem solving and other complex cognitive tasks (Scerbo et. al. 2001). While the relationship between the EEG signatures mentioned above and various cognitive states were apparent in averages across tasks and individuals, there was considerable variability in the prominence of these features for a given individual in a specific task context. In the analysis reported below, a statistical machine learning process was used to develop an individualized and task specific workload estimator to assess mental demands in each session.

5.4.3.1 Classification Approach

The spectral features that form the basis for classification contain both information pertinent to the classification of cognitive states, and irrelevant components/noise. Accurate classification of workload based on EEG calls for a system that can estimate workload by identifying dimensions or features of EEG that were informative with respect to distinctions among workload levels. A ten-fold cross-validation procedure was used in conjunction with logistic regression to identify a subspace projection that would permit discrimination between high and low workload on the basis of EEG signals.

The linear projection described above was optimized (see Figure 15) using the logistic regression technique that assumes the class conditional probability given the projection followed a logistic model,

$$f = p(c | \mathbf{x}) = \frac{e^y}{1 + e^y} = \frac{e^{w^T \mathbf{x} + b}}{1 + e^{w^T \mathbf{x} + b}} \quad (1)$$

This likelihood was parameterized by the weight vector w and bias b . The parameters were adjusted by maximizing the likelihood of the data so that the data matches the logistic model distribution in (1). The decision boundary created by this classifier was linear. Linear classifiers are widely used by EEG researchers, as their inherently low complexity limits the possibility of overfitting – an issue of concern in artifact rich mobile task contexts.

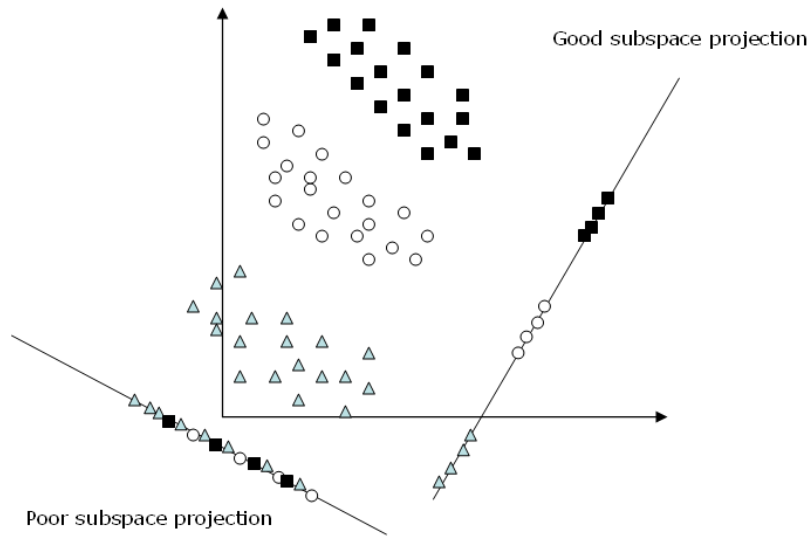


Figure 15. Example of subspace projection to optimize discrimination between classes

Under ten-fold cross-validation, the data were split into ten subsets. Over the course of ten iterations, a new subset was picked to serve as testing data, while the remaining nine folds served as the training data. This concept is illustrated in Figure 16, using three-fold and two-fold cross validation for simplicity. EEG samples from high- and low-workload conditions were used for training. Each fold left out of training was then projected onto a

set of weights identified using logistic regression in order to derive a workload estimate associated with the sample.

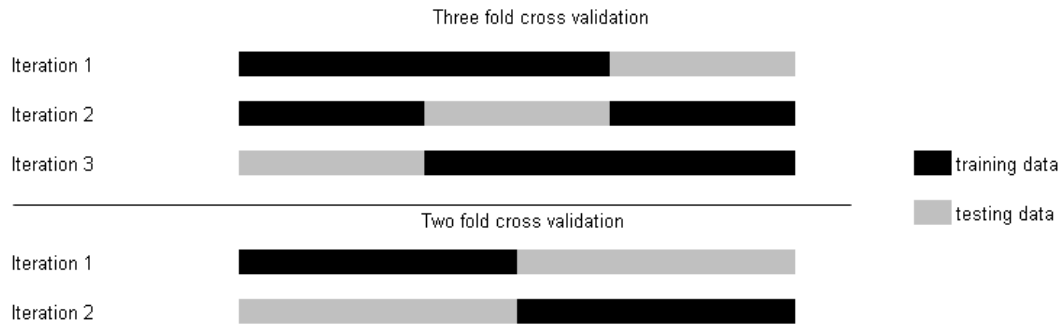


Figure 16. N-fold cross validation illustrated with n =3 and n=2.

Data were split into n equally sized segments. Over n iterations each data subset were used in turn for testing while the remaining data were used for training.

5.4.3.1.1 Classification Metric

The metric used to evaluate classification performance in this effort was the area under the ROC curve. ROC curves plot true positives (on the y-axis) against false positives (on the x-axis) as a threshold for discriminating between targets and distracters was varied. It is widely used to evaluate human and machine signal detection capabilities. The ROC curve provides a way to assess the degree of overlap between the outputs of a classifier for two classes of data. Perfect classification produces an area under the curve value (Az) of 1.0, while chance performance produces an Az value of 0.5.

5.4.3.1.2 Qualitative Analysis

As shown in the summaries of spectral features for each participant in each session (Figure 17, Figure 18, Figure 19, and Figure 20), differences in alpha stood out as the most consistent pattern across participants, sessions, and channels. Alpha power was higher in the low-workload condition. Differences in beta power were also apparent across workload conditions. But, these differences were less consistent across channels, sessions, and participants.

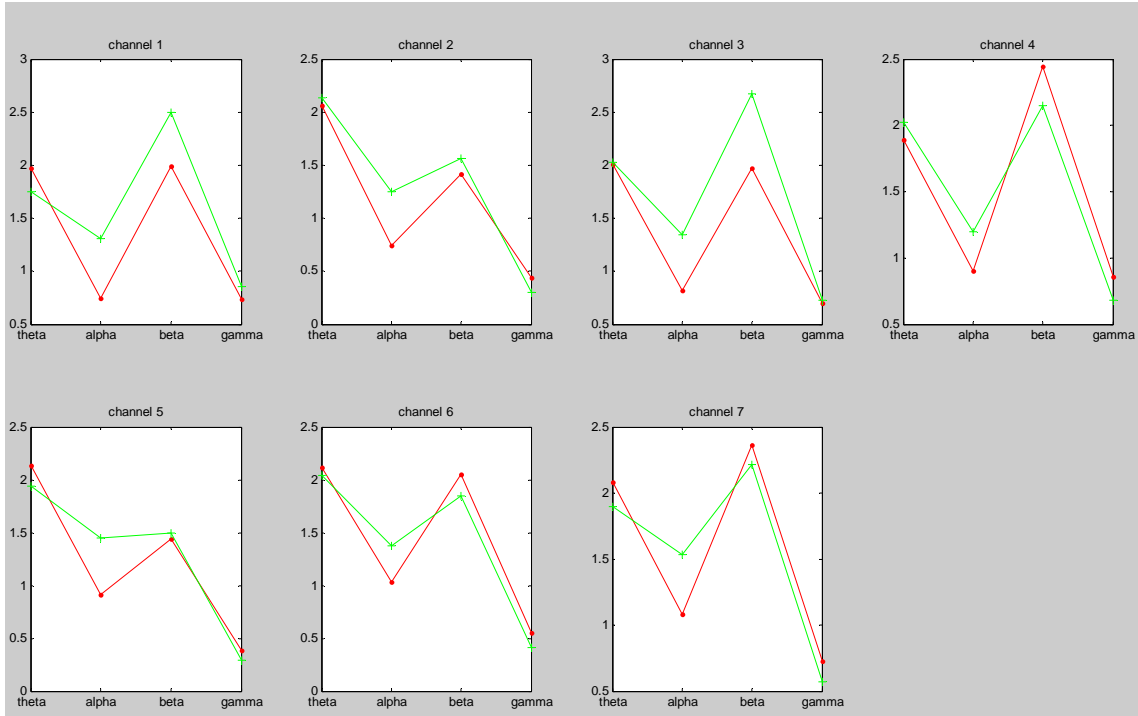


Figure 17. Participant 1- Session 1. Difference in spectral features under low (green '+') and high (red '.') workload

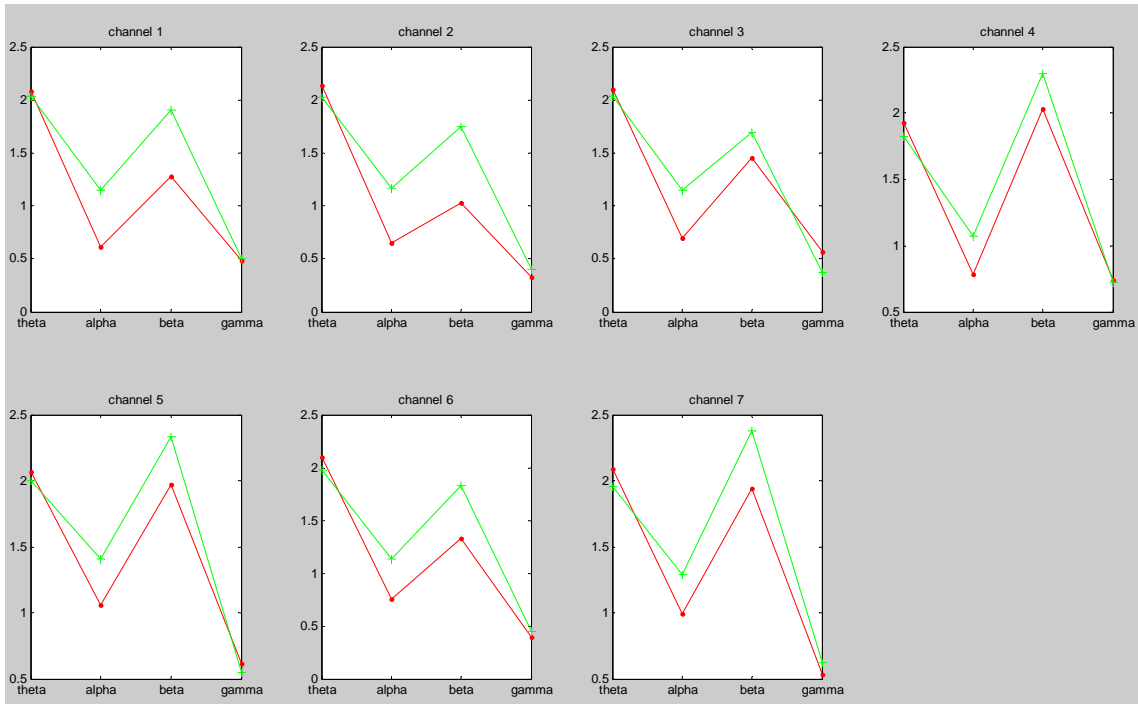


Figure 18. Participant 1- Session 2. Difference in spectral features under low (green '+') and high (red '.') workload

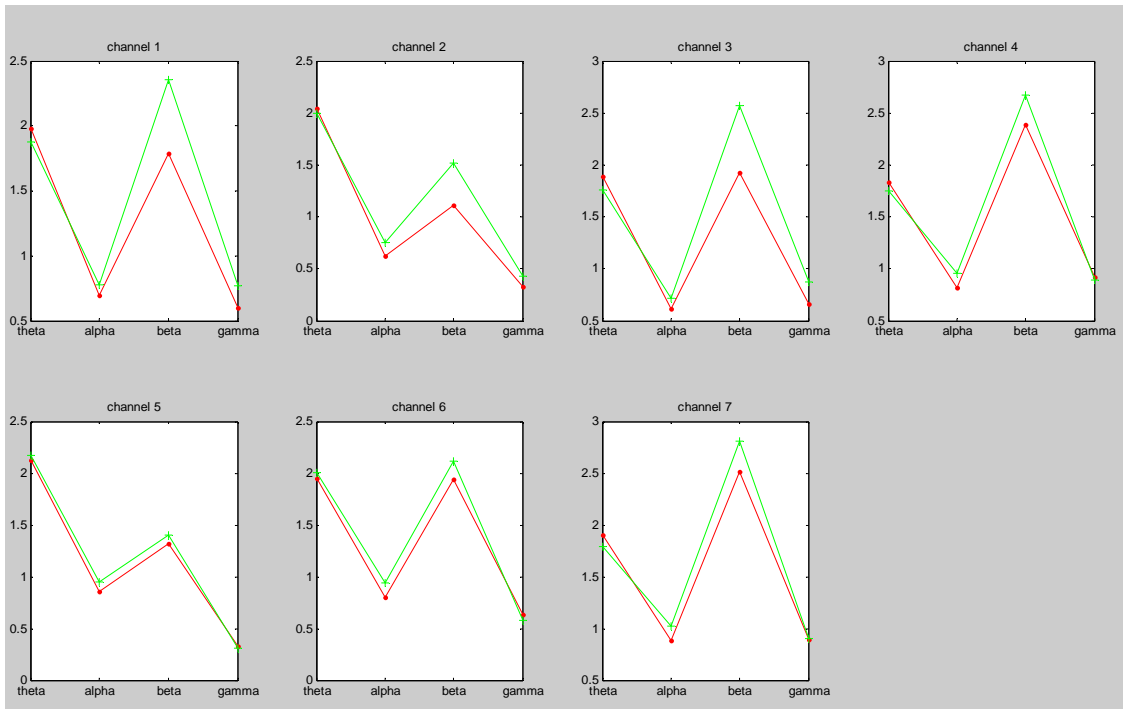


Figure 19. Participant 2- Session 1. Difference in spectral features under low (green '+') and high (red '.') workload

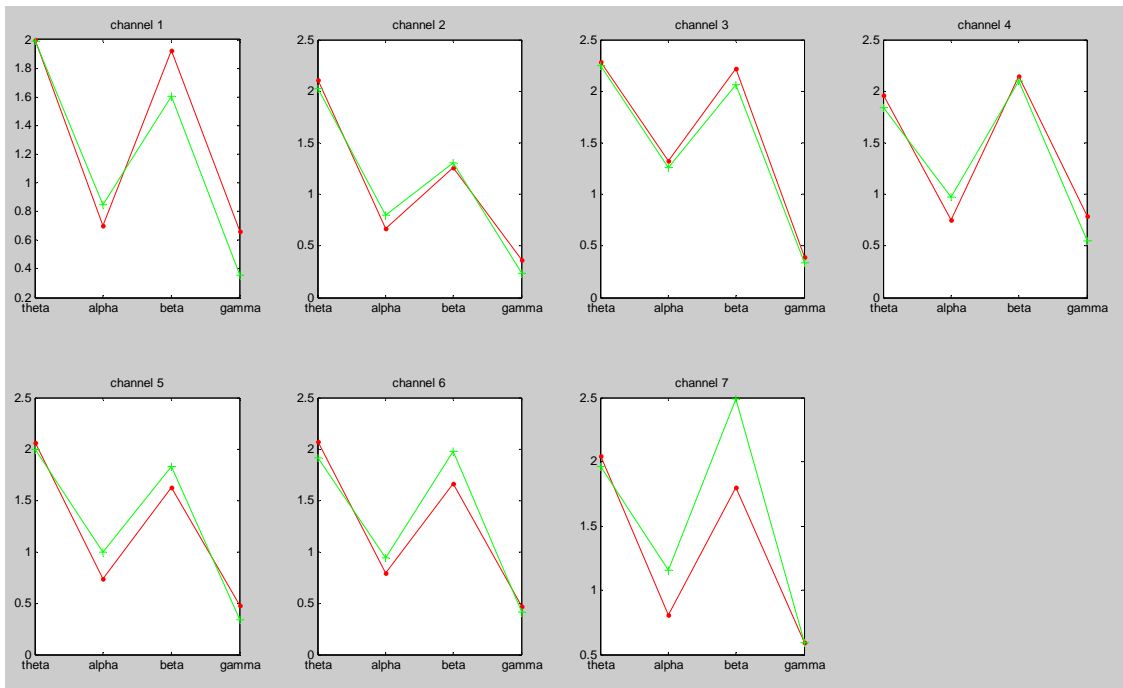


Figure 20. Participant 2- Session 2. Difference in spectral features under low (green '+') and high (red '.') workload

5.4.3.1.3 *Classification Analysis*

These classification results, as summarized in Figure 21, point to the feasibility of accurate cognitive state estimation in challenging field settings. Average base classification on a sample-by-sample basis was 0.75.

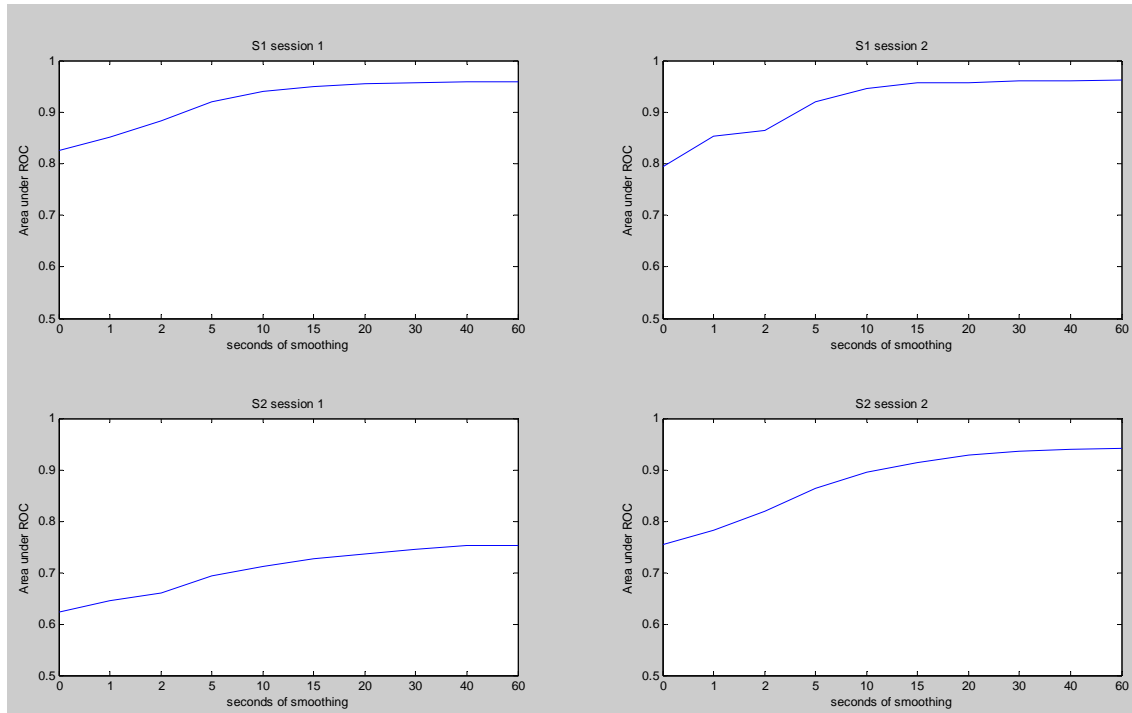


Figure 21. Classification accuracy as a function of smoothing (for both participants in both sessions)

Temporal smoothing was considered as a strategy for dealing with intermittent classification errors stemming from the noise inherent in the field environment. This strategy assumes that task demands remain stable over the span of the smoothing window. Smoothing was accomplished using a median filter on the output of the classifier over specific time windows. One consequence of temporal smoothing of classifier output is to introduce a lag in the decision process. The analysis considered the trade off in accuracy as the temporal window of output smoothing was varied.

Classification accuracy for both participants rose monotonically up to a one-minute-long temporal smoothing window. However, the rate at which temporal smoothing benefits accuracy appeared to diminish as window size increased. Temporal smoothing of ten seconds contributed to a rise in classification accuracy— average accuracy rose from 0.75 to 0.87. With the exception of Session 1 for participant 2 – classification accuracy reached .90 or higher for both participants with 10 seconds of temporal smoothing,

6 Conclusions and Next Steps

The success at FT Dix represents an advance in integration maturity for AugCog since the system was tested at the ATC in 2006. During that test, the EEG and ECG signals were transmitted wirelessly to an off-the-body system. During the OTM 2007, the sensing hardware and signal processing software were hosted on the soldier-borne FFW Leader System. Likewise, fielding dry EEG electrodes, which supported comparable classification performance to wet electrodes, was another step toward improving the deployability of a sensor-based cognitive state classification system such as the Honeywell AugCog system described in this report.

To date, the constraints of field test execution have precluded sufficient data collection to develop robust models of classification that would perform well across conditions and timeframes. Additional research is required to validate the extent to which classification models can generalize. Potential follow-up studies should require collaboration with a U.S. Army partner experienced in manipulating tonic states during long-term studies. It would be important to conduct long-term data collection in an operational environment with “ground truth” for task load, fatigue, stress, sleep deprivation, and physical load in order to develop larger data sets to support improved model development and more robust classifier performance. The goal would be to enable real-time classification approaching 90% with historical participant models. In addition, future studies could investigate classification performance as a function of tonic states and workload across multiple time frames. The feasibility of building a general classifier that works across tonic state levels should be investigated to determine whether it is necessary to build separate classifiers for each tonic state level. Finally, the fusion of slower-changing tonic state information (arousal, stress, fatigue, etc.) with faster changing moment-to-moment oscillatory EEG might yield more discriminating models.

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Appendix A

List of Acronyms

Acronym	Description
AAR	After Action Review
ABM	Advanced Brain Monitoring, Inc.
A/D	Analog-to-digital (converter)
ARL	Army Research Lab
ATC	Aberdeen Test Center
ATD	Advanced Technology Demonstration
AugCog	Augmented Cognition
BLIT	Battle Lab Integration Team
BLUFOR	Friendly (Blue) Force
C4ISR	Command, Control, Communications, Computers, Intelligence, Surveillance, and Reconnaissance
CLIP	Closed-Loop Integrated Prototype
CO	Company Commander
CONOPS	Concept of Operations
CoT	Cursor on Target
CP	Command Post
DARPA	Defense Advanced Research Projects Agency
ECG	Electrocardiogram
EEG	Electroencephalogram
EMG	Electromyogram
EOG	Electro-oculogram
ERP	Evoked Response Potential
EXFOR	Experimental Force
FCS	Future Combat Systems
FDA	Food and Drug Administration
FFT	Fast-Fourier Transform
FFW	Future Force Warrior
FRAGO	Fragmentary Orders
FT	Fire Teams
HMMWV	High Mobility Multipurpose Wheeled Vehicle
HRED	Human Research and Engineering Directorate
HVT	High-Value Target

IBI	Interbeat Interval
I/O	Input/Output
MOUT	Military Operations in Urban Terrain
NCO	Network-centric Operations
NCW	Network-centric warfare
NSRDEC	Natick Soldier Research, Development and Engineering Center
O/C	Observer/Controller
OPFOR	Opposing Force
ORP	Objective Rally Point
OTM	On-the-Move
PDA	Personal Digital Assistant
PL	Platoon Leader
PSD	Power Spectral Densities
QUASAR	Quantum Applied Science and Research
recon	Reconnaissance
RF	Radio Frequency
ROC	Receiver Operating Characteristic
RSVP	Rapid Serial Visual Presentation
RTO	Radio-Telephone Operators
SCU	Small Combat Unit
TL	Team Leader
TTP	Tactics, Techniques, and Procedures
UI	User Interface
VSDS	Vital Signs Detection System
WPSM	Wearable Physiological Status Monitor (system)
WSRT	Wearable Soldier Radio Terminal

Appendix B

Augmented Cognition System Small Unit CONOPS

B.1 General Introduction

“Network-centric warfare (NCW), now commonly called network-centric operations (NCO), is an emerging theory of war in the information age that seeks to translate an information advantage into a competitive warfighting advantage through the robust networking of well-informed geographically dispersed forces allowing new forms of organizational behavior. This “networking” utilizes information technology via a robust network to allow increased information sharing, collaboration, and shared situational awareness, which theoretically allows greater self-synchronization, speed of command, and mission effectiveness.” (Wikipedia, 2007)

The proposed system has four basic tenets:

- a. A networked force improves information sharing;
- b. Information sharing enhances quality of information and team situation awareness;
- c. Team situation awareness enables collaboration and synchronization and speed of command; and
- d. These, in turn, dramatically increase mission effectiveness.

The recently completed Future Force Warrior (FFW) Advanced Technical Demonstration (ATD) focused on NCO technology wherein members of a platoon size unit are interconnected via electronic communications. Work on the future small combat unit (SCU) maintains this same focus on communication technologies. With the advance of this technology, modern infantry platoons are evolving from tight formations with one or two radio-telephone operators (RTO) with legacy radio technology to disbursed teams where every soldier is equipped with some form of advanced digital communication device (e.g., radio-phone with display, PC tablet, Personal Digital Assistant (PDA)) (Micro Analysis & Design, 2004; Infantry Magazine, 2006). Tactically, this allows the platoon to spread out in urban environments where a platoon leader (PL) can maintain contact with his/her squad and team leaders for tactical control even under conditions of low visibility (fog, sand storms, night ops) (Future Force Warrior Small Unit CONOPS, 2005). The potential down side is that the PL will lose some immediate awareness of the soldiers’ physical and mental states normally gained from direct observation. Because effective decision making about which squad or fire team member should execute a tactical movement is often made by judging the physical and mental readiness of one’s soldiers, there will be a need to regain information lost in the new technologically based formations (Akavia & Gofer, 2006).

The AugCog system*, which originated as a Defense Advanced Research Projects Agency (DARPA) program, is designed to provide SCU leaders with real-time

* Co-joined with the Wearable Physiological Status Monitor (WPSM) system.

information on the psychophysical readiness of their soldiers. This is achieved through the use of body-worn sensors and microprocessor classification algorithms. The derived cognitive state information can then be fed to an intelligent information system directly to the leadership via the net-centric technology. Leaders will have either head-mounted displays or hand-held devices that can present graphical summaries of individual and team states of readiness. The PL will be able to maintain team situation awareness and thus control teams in broad formations and difficult terrain or conditions.

The sensors worn by soldiers are expected to be part of their uniform/equipment and will not require any special attention or care by the soldier. Thus, the system is to be a seamless component of an overarching warfighting system of systems that serves the soldier and leader and is value added versus mission demanding.

The AugCog system will not only provide current cognitive state information, but information about the recent “history” of each soldier’s cognitive state. For example, a soldier’s cognitive load may currently be low, but recent history shows an exceedingly high workload for a prolonged period, in which case that soldier may be less ready than one who has a current high workload but a recent history of low demand. Therefore, the AugCog system will indicate cognitive readiness states of individual soldiers. In addition, cognitive state feedback can be aggregated to display “Team-at-a-glance” information that allows leaders to assess a team’s combat effectiveness and readiness from a cognitive load perspective.

B.2 Assumptions

B.2.1 Assumptions Of CONOPS

The AugCog CONOPS adopts the same purpose and assumptions as established by the FFW system, as expressed in the following quote:

“CONOPS are normally developed when there is either a change in basic organizational structure of a unit ... or when new technologies and equipment are overlaid on an existing organizational structure. This is the case with FFW. The program is not creating a new organizational structure, rather FFW and its embedded technologies are being overlaid on both Stryker (Current Force) and FCS [Future Combat Systems] (Future Force) Infantry small units. For purposes of this document, a small unit is defined as Infantry Platoon and below. Although there are various uses and users of CONOPS, the primary purpose of the FFW CONOPS is to provide the vision for how systems/capabilities are operated and utilized at the small unit level.” (Future Force Warrior Small Unit CONOPS, 2005)

B.2.2 Assumptions of the AugCog System

Given the expected change of the operational mode of the FFW SCU leaders (viz., operating more remotely from subordinate units), the AugCog system provides information about unit status usually gained by direct visible contact. In addition, the system is expected to provide information about the psychophysical states of subordinates that are not normally observable. The AugCog gauges will provide internal state information about cognitive and physical readiness of key individuals that are not

always displayed in outward behaviors. And last, the AugCog system will be able to feed directly into other technologies for subsystem automation.

B.3 Mission For Net-Centric SCUs

NCW changes the way commanders look at their armies. Instead of a contest of numbers (my 3,000 troops can beat your 1,000 troops), the U.S. Army becomes one entity with many parts that can shift and adapt to quickly developing situations. Information is shared across the entire network.

According to a press release, “The Army transformation requirements includes the ability to put a combat-capable brigade anywhere in the world within 96 hours, a full division in 120 hours, and five divisions on the ground within 30 days. *One way to increase strategic agility is to allow fewer soldiers to do more work* (emphasis added).” (Grabianowski, 2007)

Thus, the concept of “fewer” may be mirrored down to companies and platoons or even lower. Companies may be sent on missions expected of battalions, and platoons may be expected to do company-sized operations. Information net-centric technology (the larger support system of small units) is expected to enable this capability. Relevant here is a statement from the 2005 FFW CONOPS about SCU missions (Future Force Warrior Small Unit CONOPS, 2005).

B.4 Operations: An Illustration

Given an assault and secure mission of an urban objective, the tasks include isolating the objective, gaining a foothold on the objective, systematically clearing rooms and structures, and finally securing and defending the isolated objective. The action begins with Fragmentary Orders (FRAGO) from the company commander (CO). However, rather than going to the company command post (CP), the PLs and staff will “meet” with the CO at the platoon site via Net-Comms. In the virtual CP, the PL obtain mission orders. PLs may interact with the CO while the squad leaders (SL) and fire team leaders (TLs) observe via their display devices.

The PLs then meet with their subordinate leaders, initially face-to-face; then, as they move to the objective rally point (ORP), they will interact increasingly via their displays and local networks, depending on unit formations and conditions. During mission execution, plans are refined as information is acquired from intelligence feeds from remote sensors, forward observers, and scouts. PLs and SLs develop and lay out specific plans of attack for their sector. SLs then meet face-to-face with their fire teams (FTs) and establish FT responsibilities. Leaders and fire team members select and prepare their equipment. Reconnaissance (recon) teams may still do “eyes-on” reconnaissance, but the PL would also get additional intelligence through remote sensors and the network. The assault may be executed as planned in a manner not too different from current tactics, techniques, and procedures (TTP), but as action and events unfold, decisions about who does what must be revised. Whereas previously PLs were co-located with many of their subordinates, in future operations where fewer soldiers conduct larger scale operations, the PL will be coordinating the mission largely through his or her communication device.

Via the AugCog systems' cognitive state feedback, the PL is able to maintain situation awareness of subordinates' mission effectiveness and current workload. As the PLs focus on display mission maps, the AugCog summary icons will help them gauge the states of the squads and fire teams.

B.5 AugCog System Characteristics

B.5.1 General Description

The system comprises a variety of sensors, which can be used individually or together as a sensor suite. The sensor suite consists of wearable (body- and head-borne), unobtrusive mobile computer systems capable of delivering clean electrocardiogram (ECG) and electroencephalogram (EEG) signals in harsh operational environments. ECG signals can be obtained from the Wearable Physiological Status Monitor (WPSM) system that would not require any additional sensing equipment. Adding EEG sensors will, however, require modification of the helmet to add dry electrodes capable of detecting EEG signals. The existing mobile computing platform will host advanced signal processing capability to improve sensor measurements. For instance, signal processing to improve heart rate (HR), HR variability, and interbeat-interval (IBI) signals can be used to improve the WPSM system and casualty care metrics.

The system provides real-time cognitive state classification processing from either ECG, EEG, or fused ECG and EEG signal components. The soldier is therefore outfitted with a mobile sensor-based ensemble that monitors states of cognitive attention and readiness during tactical movement. The system:

- Integrates sensor-driven classification of cognitive state to detect a change in the soldier's cognitive state between low-task-load and high-task-load conditions,
- Provides information about soldier cognitive states to leadership displays that reflect potential changes in operational performance,
- Uses the ECG-derived HR variability signal to reliably distinguish between different cognitive workload states,
- Can additionally use a differential EEG system to provide the EEG data required to distinguish cognitive state levels,
- Can use additional sensors (e.g., accelerometers) to improve cognitive state classification by providing context information (i.e., accelerometers to distinguish running from stationary) for understanding the cognitive state feedback.

B.5.2 Description of User Interface (UI) Display and Input/Output (I/O) Devices

Near-term application of cognitive state information utilizes a leader's ability to "close the loop" by providing PLs and a CO with real-time cognitive state information of subordinate platoon members. Displaying cognitive state information to leaders allows them to adjust the flow of communications to better match the subordinate's current capacity to process information. This mitigation strategy most closely aligns with the interests of the FFW ATD, which sees cognitive state feedback as useful information for a leader when assessing the combat readiness of his/her troops.

Cognitive state information of the subordinates is displayed to the PL or CO via the commander's display. For instance, a CO's commander's display would relay information pertaining to the cognitive state of the PL and the platoon sergeant. The CO's display might show the current real-time assessment of cognitive state via a color-coded text box, where the capacity of the soldier relative to the task demands is labeled "Unknown" (blue), "Spare Capacity" (green), "At Capacity" (yellow), or "Exceeds Capacity" (red). In addition, the history of the moment-to-moment assessment of a soldier's cognitive state is shown via a line graph. The background could be redundantly color coded to support "at a glance" processing. The scale of the timeline should be user-controllable.

In addition, aggregate measures of a team's current workload could be displayed to identify possible mismatches between expected workload and the actual workload. This would allow a leader to maintain situation awareness of the current combat readiness of groups of soldiers at a glance.

B.6 AugCog as an SCU Enabler

One of the core capabilities of the Army Transformation is the unparalleled connectivity via netted communications, enabling information sharing (Parmentola, 2004). Real-time collaboration enhances the kind of situational understanding that drives decisive actions. The inundation of information can be expected to grow between soldier and ground and air sources. The potential data overload, coupled with the efficiency of information flow required in executing Army doctrine, places an overabundance of critical information throughput on a single point of contact, the individual soldier. A means to help manage information overload of an individual soldier's mental and cognitive state is needed beyond that provided by external means (Dorneich et al., 2006).

Often it is the PL or the CO that controls the flow of information to subordinates as they manage an operation. The situation changes rapidly, requiring rapid replanning and continual updating of the current status of the soldiers, current locations, and enemy movements and intentions. The PL must understand the current capabilities of the platoon's soldiers in order to best utilize them to drive the action forward. Understanding the individuals' or team's current workload provides crucial information to the PL to rapidly deploy teams to tasks that are best suited to their current demands. In addition, knowledge of the individuals' or team's current workload allows the PL to adapt the information flow to the current capacity of the soldier to receive and understand that information.

Some training will be required to help leaders understand how to interpret and utilize cognitive workload feedback appropriately. As experience grows, it will become clear when cognitive state feedback is most useful.

B.7 Mission Operations

B.7.1 Reconnaissance

When a PL sets up a leader recon, he/she takes the risk of having some of his/her most essential platoon members clustered together, creating the potential for serious loss as they attempt to collect information about the target and the terrain. If there could be more separation among the recon team members, the risk of major team loss would be reduced. However, separation from the team reduces the PL's awareness of his soldiers' conditions and states. Remote sensors for understanding the cognitive states and conditions of the soldiers would facilitate decisions about how to move and direct the team. Workload gauges might also indicate difficult points along the approach. This all could be done with a smaller team. In fact, with sufficient sensing and communication, the PL could remain back at the ORP and direct a small recon.

If the PL is directing a leader recon remotely, he or she would use a larger display platform like a tablet PC. Given the smaller number of soldiers involved in this mission, he or she would have greater detail and more sensor information on individual team members and conditions than with a larger team (see offensive operations).

B.7.2 Offensive Operations

When a PL sets up offensive operations, he or she takes the same risks as for the leader recon. Again, if there could be more separation among team members, the risk would be reduced. Here, too, remote sensors for understanding cognitive states and conditions of key soldiers would facilitate decisions about how to move and direct the squads, and the operations could be done remotely. Workload gauges would indicate difficult paths of movement and, with other technologies for navigation, would help in decision making.

Unlike for the leader recon, the display would have less information on many of the individual team members. In fact, for multi-squad operations, the PL mainly needs the SL gauge and perhaps a summary gauge for the fire teams. A combination of the SL and the subordinate cluster information, along with radio communications, may be sufficient for the PL to "read and understand" the cognitive states of his squads. The more experience a PL has with this combined information, the better he/she would be able to build situational knowledge for offensive operations.

B.7.3 Defensive Operations

Defensive operations may not need the same level of remote sensing as either leader recon or offensive operations except on active patrols. In the case of defensive patrols, the remote sensing technology would work the same as in offensive operations.

In the case of static defenses, where there is little or no action, soldiers may become inattentive and may suffer decrements in cognitive vigilance. When the leadership is aware of this lowered state among soldiers, it interacts with them and request actions that will improve their states of alertness. This function can also be automated so as not to require action by the leaders.

B.8 Training

B.8.1 Training Requirements of System

The AugCog technology may not be totally intuitive to an untrained operator. The technology's advantage may only be realized after leaders have gained experience using it and have developed the skills to more accurately "read" the states of their men under the context and conditions of the operation. This is not unlike the situation for radar operators. Once the skill of using the technology has been acquired, the advantage of using it versus not using it will be more fully appreciated. Hence extended training will be required on this and other sensor-display technologies. Interestingly, the technology itself can be used to monitor and accelerate the training process. The workload gauges can be used to indicate where extra training may be required. The gauges may also indicate where changes might be needed in operational training. Thus, the technology will perform multiple roles.

B.8.2 Training Applications

The AugCog system can be used during training to determine the impact of training modules or routines on the development of skills. As certain skills improve, the gauges will show reductions in cognitive workload during training of specific tactical operations.

B.9 References

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Appendix C

FFW–OTM Augmented Cognition Symbolology

C.1 Objective

Definition of appropriate symbolology to represent individual soldiers and appropriate modifiers to display cognitive state assessment derived from AugCog soldier-worn systems.

C.2 References

[FFT MSIT] FFW Medical Systems Integration Team: FFW - OTM '07 Exercise: Remote Personnel Monitoring Symbolology (v1.2), 9 April 2007.

[2525B] Department of Defense Interface Standard: Common Warfighting Symbolology (MIL-STD-2525B w/CHANGE 1, 1 July 2005).

C.3 Definitions

- Electroencephalogram (EEG): neurophysiologic measurement of the electrical activity of the brain by recording from electrodes placed on the scalp.
- Electrocardiogram (ECG): physiological measurements of the electrical activity of the heart over time.
- Cognitive State Classification (CSC): real-time determination of a soldier's current cognitive workload from sensor-based (EEG and ECG) signals.
- Augmented Cognition: real-time, sensor-based cognitive state classification systems.

C.4 Strategy

Since a standard symbolology definition for the individual soldier level does not exist, the proposed symbolology for cognitive state has followed the lead of the Future Force Warrior (FFW) Medical Systems Integration Team (MSIT) approach. Since this document is modeled after the MIST draft, the symbolology proposed here is modeled after that proposed by the MSIT (see [FFT MSIT]).

C.5 Symbolology

C.5.1 Soldier Symbol

As of this report, there is no standard 2525B tactical symbol definition for the individual soldier. When a 2525B symbol is defined and is used for specific soldiers, the 2525B definition will take precedence. But for the FFW OTM 2007, the new generic soldier symbolology proposed by the FFW MSIT was used (Figure C-1).

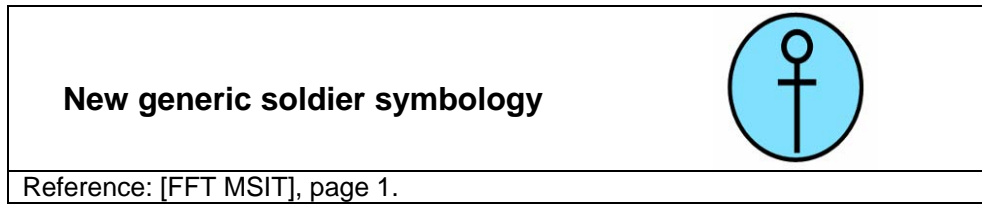


Figure C-1. New generic soldier symbology.

The features of the symbol (listed in Table C-1) will follow the MIL-STD-2525B specification for the composition of tactical symbols (2525B, section 5.4, page 46). See this specification for definitions of the form and fill of the proposed individual soldier.

Table C-1. Feature specifications for the soldier symbol.

Feature	Specification	Reference
Frame	Circle for the individual soldier.	[FFW MSIT]
Affiliation	Friend (only). Since there is no cognitive state classification information on non-friendly forces, "Friend" is the only affiliation.	[2525B], Section 5.3.1.1, page 48
Fill	Crystal Blue (128,224,255) for friendly affiliation.	[2525B], Table XIII, page 51
Icon	Person icon illustrated in Figure C-1	[FFW MSIT], page 1.
ID	"...the tactical ID for each soldier needs to be appended to his individual symbol to ensure that he can be properly identified on the Common Operating Picture. Since this is a tactical requirement rather than medical specific, that tactical ID will be appended to this symbol."	[FFW MSIT], page 1.

C.5.2 Healthy Soldier

When the combat effective soldier has a fully functioning CSC system and the CSC does not detect any elevated cognitive workload states, then no alert is generated. In this case, the default soldier symbol is used, without modifiers. It is anticipated that this will be the most frequently used symbol.

C.5.3 Cognitive State Alerts

In monitoring cognitive state, the CSC system will continually assess the soldier's physiology (ECG) and neurophysiology (EEG). Computer algorithms will process the data to determine:

- (a) whether soldier is operating under increased cognitive workload and
- (b) whether the CSC system itself is working properly.

If the CSC system is working properly and it detects that the soldier is operating under increased workload, the computer algorithms will generate and transmit the appropriate status alert (i.e., Medium or High workload).

The modifier for the appropriate CSC status alert will be appended to the lower right corner as the “K” modifier. The “K” modifier is designated for Combat Effectiveness ([2525B], Table IV, page 52). Form, length, and coloring will follow MIL-STD-2525B. The modifier is placed in a small text box to allow background color coding to emphasize the distinction between the levels of the CSC status alerts.

C.5.4 System Fault Alert

If at any point the soldier’s CSC system itself is not functioning properly, a modifier for the modifier for the CSC system fault alert will be appended to the symbol on the middle of the right side as the “H” modifier. The “H” modifier is designated for Additional Information ([2525B], Table IV, page 52). This alert needs to be distinct from other defined alerts.

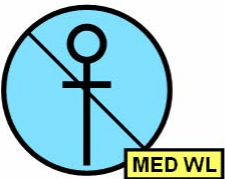
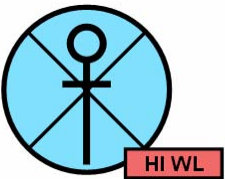
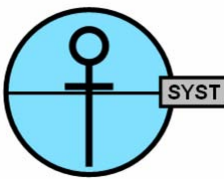
C.5.5 Unit Roll-Up

For the FFW OTM 2007, there will be no unit roll-up since only one soldier will be equipped with the CSC system.

C.5.6 Final Composite Symbols

Table C-2 illustrates the tactical symbols for cognitive state feedback.

Table C-2. Tactical symbols for cognitive state feedback.

State	Cognitive State: Medium Workload	Cognitive State: High Workload	CSC System Fault Alert
Symbol			

C.6 System Logic

Figure C-2 illustrates the system logic of the CSC system.

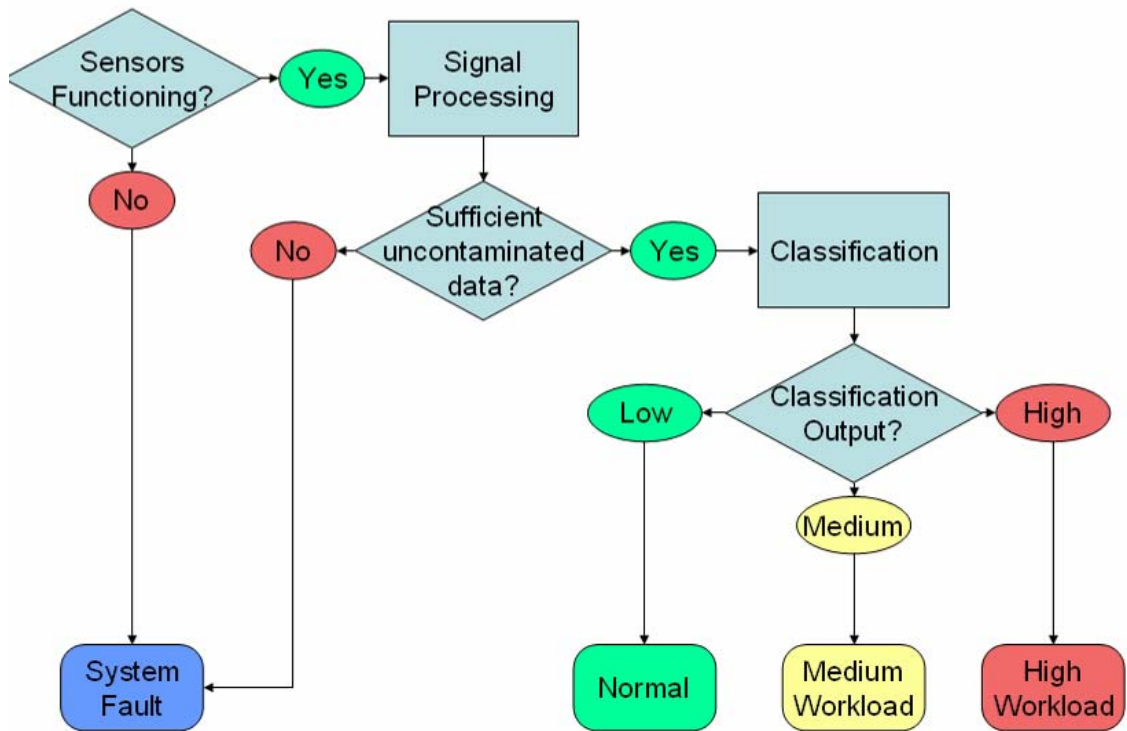


Figure C-2. CSC system logic.